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Design & Development of Booster Techniques Using Machine Learning Algorithms for BSE

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1. Introduction

The Indian economy, with its constantly rising and expanding GDP, is regarded as a global economic growth engine. A strong economy's stock market serves as the public face of the expanding industry and its businesses. In essence, the stock market is an electronic marketplace where stock prices are listed and exchanged. Companies can now successfully and efficiently raise funds from the public, thanks to this cutting-edge platform. In India, the Bombay Stock Exchange and the National Stock Exchange are the two major stock exchanges. BSE is the oldest and NSE fastest-growing stock market platform. The country's economic reforms have led to an exponential increase in foreign institutional investment and transaction volume on stock exchanges.

There were many stocks migrated from offline to online trading, especially in the Indian Stock Market, and as a result of this growth story, the market capitalization has crossed 4.33 Trillion by 22 January 2024. India is the fourth biggest market in the world behind only the US, China and Japan. More than 2000 companies are listed with NSE, and over 5000 stocks are traded under Bombay Stock Exchange (BSE) making the Indian market most attractive in offering wide investment opportunities to domestic as well international traders. India's GDP is going to touch $5 trillion mark by the year 2024-2025 as predicted by the Union Minister of Petroleum Mr. Hardeep Puri and in another 6-7 years it is going to double to $10 trillion.

Organizations can raise capital through the stock market to fund their expansion or growth. In this case, an organization must transfer ownership to third parties through shares or stock. This is handled by the organization via the IPO process. The general public can purchase or sell these equities through stock exchanges. It is believed that the stock market has a variety of characteristics. Stakeholders are individuals or groups with an interest in the stock market and who profit from it in some way. Organization promoters, domestic and foreign institutional investors, retail investors, stock brokers, and investment consulting firms are some of the main stakeholders in Stock Markets.

Since the stock price is dependent on a number of variables, the majority of which are unpredictable, its movement is non-linear, non-stationary, and noisy. The demand and supply of stocks, management of the company, rivalry from rivals, national policy, the policy of the central bank of the nation, and any news pertaining to the company can all affect the price of the stock.

Buying, selling, or holding stock of companies listed on exchange is available through trading options. A market area for traders to purchase and sell equities is the stock exchange.

Government regulation of stock markets is in place in many countries. There are two methods to benefit from the stock market: investing and trading. Although traders and investors both want to make money, their goals are not the same. An investor with a year-to-multi-year stock holding duration adopts a long-term perspective based on the company's prospects and long-term trends. On the other hand, traders who retain their stock for a few days or hours buy and sell it depending on the short-term trend.

The investors use and implement a variety of strategies. The best course of action depends on the investor's risk tolerance and understanding pattern of market. The price, volatility, and marketability of the underlying asset are other factors that affect trading strategy. Directional and non-directional strategies are the general categories into which these methods fall.

When an investor is convinced about the near-term direction of the market or security, they will utilize directional techniques. It refers to a strategy wherein one takes a long position when the market or security is expected to go up or a short position when the market or security is expected to fall. Based on market patterns, these strategies are either Bullish or Bearish.

Based on the company's fundamentals, such as its yearly growth rate, annual return, sector performance, and management, investors forecast the long-term trend of the stock known as fundamental analysis. Technical analysis is used by the trader to forecast the stock's short-term trend. Technical analysis uses a variety of indicators, including moving averages, to forecast short-term trends based on historical data. This argument focuses solely on trading not investing.

Analysis in this study is solely based on data. Based on data from past and present trading sessions, trading methods can be implemented. Unlike the company's management performance or the national economy, fundamental analysis is not used. It requires a short-term view to make trading judgments because trading strategies are appropriate for short-term trading. Technical analysis is useful for short-term trends.

The proposed research model strategies do not depend on a stock market's long-term trend, hence fundamental analysis has not been utilized in research.The research model automates the decision-making process, which in a result quickly and efficiently executes trading strategies rather than manual trading.

After the successful development of the model, it can be tailored for options trading, high-frequency trading, and also portfolio optimization

2. Purpose of the Study

Nowadays, Algorithmic trading is essential, as it plays an important role in the financial market. It processes huge amounts of data within the millisecond and reduces the risk of losses. The purpose of carrying out the research is to reduce human involvement in the market, human beings cannot constantly watch the market, and there must be some systematic way to trade in the market. Human makes a lot of errors in trading and investing. Also, there is always an emotional and cognitive human bias involved in trading. To reduce such human bias and generate the best return for investors, traders are the ultimate purpose. The reduced risk while trading in the market identifies different types of trends and patterns in the market. To test the algorithmic developed model and simulate it. The model can be scaled across different instruments of the market, to automate trading and execute it in real-time. Over a period of time, the performance of algorithmic strategy gets reduced as the dynamics of the market change, to reduce the degradation in performance and build dynamic strategy.

3. Survey or review of literature

The time series data is forecasted using the Hidden Markov Model (HMM).The next day's stock price was predicted [1]using HMM. In order to forecast the stock price for the following day, they trained a continuous HMM utilising variations in the stock close, low, and high values in relation to the open value throughout a daily session. They trained four distinct models for four distinct equities and experimented with their model on those stocks. When compared against the ARIMA, HMM-fuzzy, and ANN models, the suggested model fared well.

The data was gathered from NSE.com, according to Devi et al.[2] . For analysis, historical data covering the five years from 2007 to 2011 was considered. Model identification is done using the Box-Jenkins methodology. The best model is chosen by applying the AICBIC test criteria against the data shown in the previous. For all indices, the optimal model equation is found. The difference between the forecasted and actual historical data is ascertained by using the MAPE, PMAD, and % Error accuracy.

The optimization of portfolios has made substantial use of reinforcement learning (RL)[3]. An important work suggests using expected maximum drawdown (E(MDD)) as a downside risk metric in recurrent reinforcement learning (RRL). Particularly in long/short portfolios under various transaction cost situations, this method beats conventional RRL methods utilizing the Sharpe and Sterling ratios. In order to improve its responsiveness to market conditions and

transaction costs, the adaptive E(MDD) risk-based RRL system additionally incorporates a stop-loss retraining mechanism.

The incorporation of reinforcement learning and neural networks, in particular, has allowed algorithmic trading systems to achieve even greater advancements in capabilities [4]. Neural networks are highly accurate in predicting price changes and modeling complex market behaviors. For instance, a self-evolving trading strategy for commodities futures was created using a back propagation neural network, and it beat conventional techniques in terms of yield and risk management.
Another strategy combines techniques for portfolio selection with machine learning classifiers[5]. Significant gains in day trading investments were shown by a fusion model that used support vector machines (SVM) for trend classification and machine learning (MV) for portfolio selection.

Technical analysis, textual analysis, and high-frequency trading are the three main areas into which algorithmic trading systems can be divided. There are benefits and drawbacks specific to each of these approaches[6]. In order to forecast future price changes, technical analysis relies on historical price data and trading volumes. While high-frequency trading concentrates on executing a large number of trades at extremely high speeds in order to capitalize on small price disparities, textual analytics utilize natural language processing to assess sentiment from news and social media.

To improve prediction accuracy, a number of studies have concentrated on combining sophisticated feature engineering methods with deep learning models [7]. For example, Multi-Filters Neural Network (MFNN) is a revolutionary end-to-end model presented for price movement prediction and feature extraction. In terms of accuracy, stability, and profitability, this model outperforms single-structure networks and conventional machine-learning models by integrating convolutional and recurrent neurons to capture data from various feature spaces and market perspectives.

According to Mankar et al.'s proposal[8], which was based on a comparative analysis we conducted, The Support Vector Machine is the most practical and effective model for forecasting stock price movement in line with data sentiments. When we receive the data straight via the REST API, cloud services will allow us to gather vast amounts of data. Data

that is categorized as happy, negative, or neutral provides a useful picture of the general public's mood. After further research, other variables influencing public sentiment will be examined and included to the system.

According to Dang et al. [9], a lot of academics and investors are interested in the topic of stock trend prediction using deep learning because of the potential for significant profit margins due to increased prediction accuracy. Two-stream Gated Recurrent Unit (TGRU) achieved an overall accuracy of 66.32%, surpassing the performance of the previous model, which included GRU and LSTM. The text processing have learning states: forward and backward. Harvard IV-4 sentiment dictionary and financial information are used to generate the Stock2Vec embedding.

For portfolio management, the authors proposed a two-stage deep-learning approach [10]. Additionally, absolute and relative returns were computed using the cost function. Their model outperforms common deep learning models in terms of performance using traditional machine learning techniques. They used exchange-traded funds to test their model.

CNN was utilized by the authors of Alonso-Monsalve et al. [11] to forecast the one-minute trend of cryptocurrency exchange rates. They conducted tests using the six well-known cryptocurrencies. To train the suggested models, they created eighteen technical indicators using trading data of bitcoin exchange rates. Four models are compared: the hybrid Convolutional LSTM, the convolutional neural network, the standard multilayer perceptron, and the radial basis function neural network.

The effectiveness of different deep learning architectures in stock price prediction has been compared in research. SP 500 database of five sectors Consumer Cyclical, Communication Services, Energy, Healthcare, and Technology used in the study. In the study, the price of S&P 500 markets stocks is predicted using six different models: MLP, CNN, RNN, LSTM, GRU, and AE [12]. Notwithstanding the fact that CNN occasionally outperformed other models, the results shed light on how useful these models are in the financial markets.

Modifying feature engineering when combined with deep learning models was another all-encompassing strategy used to forecast stock market trends [13]. By pre-processing the dataset,

applying various feature engineering approaches, and using a customized deep learning model, the system was able to anticipate stock market trends with a high degree of accuracy.

In terms of return prediction and portfolio optimisation, machine learning (ML) and deep learning (DL) algorithms have demonstrated considerable potential [14]. In a study, mean-variance (MV) optimisation (RF+MVF) was found to outperform other models when return prediction was paired with random forest (RF) and support vector regression (SVR) models, as well as deep learning models like LSTM and convolutional neural networks.

Conversely, trading machines can learn the best trading tactics through market interaction through reinforcement learning [15]. Trading agents that can adjust to shifting market conditions and generate long-term profits have been created using methods like Q-learning and deep reinforcement learning

An actor-critic architecture-based deep reinforcement learning algorithm is presented [16]. By maximizing a weighted sum of predicted returns and value at risk (VaR), this model optimises portfolio weights. When compared to benchmark strategies, the use of quantile regression to learn the distribution of portfolio returns and a multi-process strategy for training acceleration shows greater performance in backtesting.

The integration of sentiment analysis into deep learning models has demonstrated encouraging outcomes [17]. To anticipate the stock values of significant Indian companies, for instance, a study included macroeconomic indicators, sentiment data gathered with an Intensity Analyser and LSTM models with historical prices.

The study [18]demonstrates machine learning frameworks for algorithmic trading methods in the US stock market. The XG-Boost algorithm produced the best R-squared and accuracy results.

Table I. Existing literature work for the Stock market Predication with different methodologies & techniques

Sr. No.	Author	Title	Year	Methodology/ Techniques	Testing/Dataset	Limitation/ Future Scope
1	Aditya Gupta et al.	Ref. [1]	2012	Maximum a posteriori (MAP) HMM approach, HMM approach is compared with other forecasting methods, including HMM-fuzzy models, ARIMA, and Artificial Neural Networks (ANNs)	Algorithm was tested on four different stocks indices – Dell, IBM TATA steel and Apple	The correlation between stock is not considered, minute by minute granular data may be used to explore future work
2	B. Uma Devi et al.	Ref. [2]	2013	ARIMA model for stock trend prediction, Nifty Midcap50 companies Historical data are used	NSE-Nifty Midcap50	Time series analysis with only specific period of trends in market is considered.
3	Saud Almahdi et al.	Ref. [3]	2017	ANN based trading decision system with reinforcement learning. Recurrent reinforcement learning for optimization.	Exchange Traded Fund of IWD: iShares Russell 1000 Value IWC: iShares Micro-Cap SPY: SPDR S&P 500 ETF DEM: WisdomTree Emerging Markets High Dividend CLY: iShares 10+ Year Credit Bond	RRL model can be extended by adding extra layer, Tracking errors can be minimized with help of RSI
4	Shenyong Xiao et al.	Ref. [4]	2017	Back Propagation neural network model for commodity futures price prediction, Utilizes High-frequency one-minute intervals data	Data from Shanghai and Dalian Futures Exchanges	The predictive performance of the model is affected by muted peaks and troughs of data. Applied for few commodity
5	Felipe Dias Paiva et al.	Ref. [5]	2018	Decision-making model Mean-variance methods and SVM are used,	Sao Paulo Stock Exchange	Only one Ibovespa index is considered for the study, Stop-loss mechanisms is not implemented

				Fusion approach with multiple machine learning methods.		
6	Boming Huang et al.	Ref. [6]	2018	Categorizes methods into textual, technical, and high-frequency trading, Advantages and disadvantages of each method are evaluated. A role of qualitative information in behavioral finance is discussed	Ibovespa index, News articles, blogs, and social media. Google Trends data .	Unresolved issues and Future research direction are identified
7	Wen Long et al.	Ref. [7]	2018	Multi-filters neural network (MFNN) model, MFNN integrates convolutional and recurrent neurons	Chinese stock market index CSI 300	High-quality features have a significant impact on the models' performance.
8	Tejas Mankar et al.	Ref. [8]	2018	Stock market prediction using social sentiments. Tweets are analyzed for sentiment analysis using ML techniques. Support Vector Machine is the preferred predictive model.	Tweets collected using Twitter API, Stocks closing values	News events, public mood can be added, Historical Twitter data can be added
9	Dang Lien Minh et al.	Ref. [9]	2018	Two-stream GRU for stock price prediction. Utilizes sentiment analysis and financial news for predictions. Stock2Vec is introduced	S&P 500 and VN-index stock prices	Long-term sentiment, trends are not captured. Huge computational resources and long training are needed
10	Hyungbin Yun et al.	Ref. [10]	2019	Joint cost function for model training Two-stage deep learning method for portfolio management	ETF price data from 32 countries included in the MSCI ACWI covering approximately 15 years from Yahoo finance	Advanced deep learning methods such as LSTM and CNN are not used

11	Saul Alonso Monsalve et al.	Ref. [11]	2020	Neural networks for cryptocurrency CNN, CLSTM, MLP, and RBFNN architectures	Six cryptocurrencies data like Bitcoin, Dash, Ether, Litecoin, Monero, Ripple	Due to computational cost only one year of the dataset is considered
12	Van-Thang Duong et al.	Ref. [12]	2020	MLP, CNN, RNN, LSTM, GRU, AE model are evaluated LSTM is mostly used for sequential data	SP 500 database of five sectors Consumer Cyclical, Communication Services, Energy, Healthcare, and Technology	The choice of models depends on the Sector
13	Jingyi Shen et al.	Ref. [13]	2020	Short-term trend price prediction. State-of-the-art prediction model	3558 stocks from the Chinese stock market.	Sector capitalization constraints and transaction costs are not addressed
14	Yilin Ma et al.	Ref. [14]	2020	Support Vector Regression and Random Forest are key predictive models RF+MVF are recommended for daily trading	China Securities 100 Index, including 49 stocks	Technical indicators, News sentiment, and Economic factors are not incorporated
15	Jigdish Chakole et al.	Ref. [15]	2021	Q-learning agent for automated trading Two models for state representation are proposed	Dataset includes stocks from NASDAQ, DJIA, NIFTY, and SENSEX	Sophisticated data preprocessing methods like feature selection and extraction are not implemented
16	Boyi Jin et al.	Ref. [16]	2022	Employs an Actor-Critic architecture for optimization Improved deep reinforcement learning algorithm are utilized	Data from Yahoo Finance ETF of US ORCL, AAPL, TSLA, and GOOG companies	Communication between the market environment and the trading agent takes lot of time
17	Narayana Darapaneni et al.	Ref. [17]	2022	LSTM and Random Forest are employed RMSE was used as the evaluation metric	Yahoo Finance Historical data Sentiment data from various public news sources.	Daily sentiment calculation may dilute strong sentiments
18	Nisha Gurung et al	Ref. [18]	2024	XG-Boost algorithm Ridge Regression AdaBoost model Linear Regression Model Cat-boost Model	Amazon's stock data	The impact of market volatility on predictions is not discussed

4. Research Gap

- The majority of research is done outside of India.
- A trading strategy should be dynamic whereas a static trading strategy is not reliable.
- In SVM, a number of optimal features are unable to be pointed out by the feature selection method and hence the accuracy of the system is affected.
- The deep learning framework-based devised CNN was not suitable for highly extensive applications.
- The effectiveness of traditional trading strategies decreases with time.
- Precise second-by-second data is not studied for the development of a model.
- Risk is not properly managed or controlled.

5. Importance of the study

The study is important since global securities investments are growing at an unprecedented rate. These models process huge volumes of historical and live data to help find patterns, trends, or future outcomes so an investor can make more informed decisions about which investment opportunity to pursue. Traders create trading strategies that trade automatically, based on these predictive signals derived from stock prediction models, like the one we will be building. Such automation can lead to an increase in trading efficiency and minimize human errors.

At an international level, algorithmic trading has a turnover of more than $20.52 billion, it is expected that it may cross $33.87 billion by the end of 2027. U. S. & China are significant contributors due to innovation in the regulatory environment and financial market. In Emerging countries like India, 50% of trading is done using an algorithm

As it controls emotion and the bias of humans, it has numerous applications in AI and data science. Thus overall financial prediction is improved.

6. Objectives

Algorithms and computers are frequently utilized in stock market decision-making. Computers are taught to learn from historical data obtained through various sources without human involvement. Machine learning algorithms have the ability to make profitable decisions and so forth. Providing answers to some of these queries is our aim for this study.

- Critical study of the current equities transaction data from the NSE and BSE.
- To implement a methodology for Deep Learning, and Machine Learning using multiple models.

- To investigate the models at various lag intervals to determine which one performs optimally in emerging markets in India, where market fluctuations are considerable.
- Training an algorithmic trading agent to make trading decisions, such as whether to buy, sell, or hold shares, to perform final decision.
- Performance evaluation of automate trading process which maximize profitability, enhance speed and efficiency, and improve prediction accuracy.

7. Research Methodology

The use of algorithmic trading to execute trade offers several advantages over manual trading, as it executes a trade in milliseconds, and there is no emotional bias attached while making a decision. The algorithmic strategy can be back-tested and optimized. Consistency and discipline is maintained, and manual errors are eliminated. A strategy can be scaled across global beyond human capacity. The algorithm can continuously monitor the market without break.

The proposed study focuses on implementing different machine learning algorithms and developing the best model that will boost the overall return of investors. To design such a robust algorithmic model, Scholars and researchers are always interested in historical stock data and market-related news data. Some work, such as data preprocessing is required to be done for the purpose of prediction task.

The stock market in India has nearly 7000 firms listed on the public exchanges NSE and BSE for trading purposes. Exchange facilities, either real or virtual, are available for trading between buyers and sellers. Price discovery is made possible by exchanges. Large amounts of data are generated for the trades that occur on the stock exchange during the transaction. This data is helpful for researchers to determine the relationships between various stocks of Indian stock markets. The data is gathered from free secondary online sources. Data has several key attributes set that make up data like date, open, low, high, close, and WAP values. The gathered data might include inaccurate or unnecessary information that has no bearing on the research project. This kind of information will be recognized and formatted appropriately so that data mining can be done using the tools that are most appropriate for the research issue. One kind of data format that is accessible from the collection work is converted into a desired format so that the analysis can be performed on it as part of the preprocessing of data. A comma-separated value (csv) file is typically used to store stock data. This file may include information on the

stock's name, opening price, low price, high price, closing price from the previous day, quantity traded, trade date, total turnover, no. of Shares, and no. of trades

A Typical Algorithm trading is implemented using Python programming language shown in Fig. 1. Historical data as well as live market data is obtained as needed. Stock cleaning and

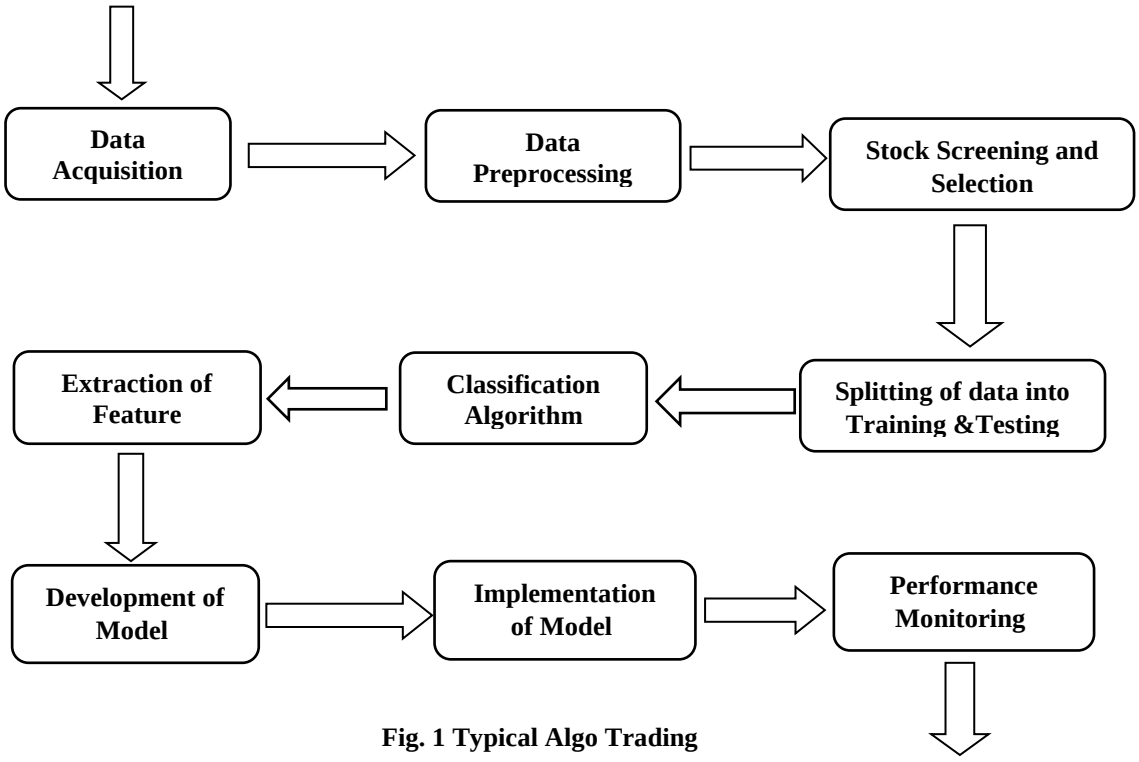

Fig. 1 Typical Algo Trading

selection is done Data preprocessing, data that has been downloaded is cleaned, transformed, and made available for further analysis. Cleaned data is split into training and testing. There are different classification algorithms like Linear regression, Logistic regression, Decision trees, Naive Bayes, Random forest, Deep learning and Support Vector Machines. To build a robust model the algorithm that produces the best result is selected. From the available data, new characteristics useful for the strategy are extracted. Using Python libraries a model is developed based on a number of parameters like fundamental analysis, and technical indicators. The algorithm takes care of continuous condition checking, monitoring, and evaluation of live trading strategy known as performance monitoring.

This model is developed using Python programming language. For implementation purposes, different libraries of Python are used like websocket-client, smartapi-python, pycrypto, cryptography, etc.

The machine learning algorithms used in research are as:

- Linear Regression: A direct way to simulate the relationship between more than one characteristic and stock price is known as linear regression.
- Support Vector Machines (SVM): SVM can identify patterns in stock price movements, which makes it appropriate for regression and classification applications.
- Random Forests: An ensemble method that bundles multiple decision trees to model complex patterns in data.
- Neural Networks LSTM (Long Short-Term Memory) networks are popular for time series forecasting.
- XGBoost: It is a powerful gradient boosting system that excels in prediction applications such as those used in regression, and manages big datasets.
- Reinforcement Learning: Algorithm like Q-learning can be implemented to create Trading strategies based on Stock price predictions.
- Time Series usually utilizes statistical techniques, such as the conventional ARIMA (Auto Regressive Integrated Moving Average) model.

The best classification algorithm is selected to build a robust model.

8. Limitation

- Model always depends on the quality of the data, incorrect data leads to incorrect prediction.
- An undetermined or black swan event can be handled by the model.
- Due to technical glitches a developed model may not work in some situations.
- The market dynamic is always changing after a certain period of time thus if affects model performance.

9. Expected Outcome

- The emotional and cognitive bias toward trade will be reduced.
- Overall return on investment and risk management will be improved.
- A diversification of portfolio stock and real-time adjustment of trade will be improved.
- Transparency in trade and the disciplinary approach of traders or investors will be improved over the manual approach.

10. Yearwise Plan

Year-1	Year-2	Year-3
Finalize Project Description		
Literature study		
The use of theoretical analysis to current procedures to enhance stock market analysis.		
Journal article -I		
	Literature study	
	Design and implementation of Algorithm using various techniques.	
	Data collection and pre-processing of data analysis in the stock market.	
	Performance evaluation & analysis of experimental result	
	Journal article -II	
		Interpretation & result analysis of experiments
		Journal article -III
		Final synopsis and thesis Preparation
		Synopsis and Thesis Submission & Defence

11. References

[1] A. Gupta and B. Dhingra, "Stock market prediction using Hidden Markov Models," in *2012 Students Conference on Engineering and Systems, SCES 2012*, Sep. 2012, pp. 1–4. doi: 10.1109/SCES.2012.6199099.

[2] U. D. B, S. D, and A. P, "An Effective Time Series Analysis for Stock Trend Prediction Using ARIMA Model for Nifty Midcap-50," *International Journal of Data Mining & Knowledge Management Process*, vol. 3, no. 1, pp. 65–78, Jan. 2013, doi: 10.5121/ijdkp.2013.3106.

[3] S. Almahdi and S. Y. Yang, "An adaptive portfolio trading system: A risk-return portfolio optimization using recurrent reinforcement learning with expected maximum drawdown," *Expert Syst. Appl.*, vol. 87, pp. 267–279, 2017, doi: 10.1016/j.eswa.2017.06.023.

[4] S. Xiao, H. Yu, Y. Wu, Z. Peng, and Y. Zhang, "Self-evolving trading strategy integrating Internet of Things and big data," *IEEE Internet Things J*, vol. 5, no. 4, pp. 2518–2525, Aug. 2018, doi: 10.1109/JIOT.2017.2764957.

[5] F. D. Paiva, R. N. Cardoso, G. P. Hanaoka, and W. M. Duarte, "Decision-making for financial trading: A fusion approach of machine learning and portfolio selection," *Expert Syst. Appl.*, vol. 115, pp. 635–655, 2019, doi: 10.1016/j.eswa.2018.08.003.

[6] B. Huang, Y. Huan, L. Xu, L. Zheng, and Z. Zou, "Automated trading systems statistical and machine learning methods and hardware implementation: a survey," *Enterp Inf Syst*, vol. 13, pp. 132–144, 2018, doi: 10.1080/17517575.2018.1493145.

[7] W. Long, Z. Lu, and L. Cui, "Deep learning-based feature engineering for stock price movement prediction," *Knowl. Based Syst.*, vol. 164, pp. 163–173, 2019, doi: 10.1016/j.knosys.2018.10.034.

[8] T. Mankar, T. Hotchandani, M. Madhwani, A. Chidrawar, and C. S. Lifna, "Stock Market Prediction based on Social Sentiments using Machine Learning," in *2018 International Conference on Smart City and Emerging Technology, ICSCET 2018*, Institute of Electrical and Electronics Engineers Inc., Nov. 2018. doi: 10.1109/ICSCET.2018.8537242.

[9] D. Lien Minh, A. Sadeghi-Niaraki, H. D. Huy, K. Min, and H. Moon, "Deep learning approach for short-term stock trends prediction based on two-stream gated recurrent unit network," *IEEE Access*, vol. 6, pp. 55392–55404, Sep. 2018, doi: 10.1109/ACCESS.2018.2868970.

[10] H. Yun, M. Lee, Y. S. Kang, and J. Seok, "Portfolio management via two-stage deep learning with a joint cost," *Expert Syst Appl*, vol. 143, Apr. 2020, doi: 10.1016/j.eswa.2019.113041.

[11] S. Alonso-Monsalve, A. L. Suárez-Cetrulo, A. Cervantes, and D. Quintana, "Convolution on neural networks for high-frequency trend prediction of cryptocurrency exchange rates using technical indicators," *Expert Syst Appl*, vol. 149, Jul. 2020, doi: 10.1016/j.eswa.2020.113250.

[12] V.-T. Duong, D.-T.-A. Nguyen, T.-T.-H. Pham, V.-H. Nguyen, and V.-Q. A. Le, "Comparative Study of Deep Learning Models for Predicting Stock Prices," in *Proceedings of the Seventh International Conference on Research in Intelligent and Computing in Engineering*, PTI, Mar. 2023, pp. 103–108. doi: 10.15439/2022r02.

[13] J. Shen and M. O. Shafiq, "Short-term stock market price trend prediction using a comprehensive deep learning system," *J Big Data*, vol. 7, no. 1, Dec. 2020, doi: 10.1186/s40537-020-00333-6.

[14] Y. Ma, R. Han, and W. Wang, "Portfolio optimization with return prediction using deep learning and machine learning," *Expert Syst. Appl.*, vol. 165, p. 113973, 2021, doi: 10.1016/j.eswa.2020.113973.

[15] J. Chakole, M. S. Kolhe, G. D. Mahapurush, A. Yadav, and M. Kurhekar, "A Q-learning agent for automated trading in equity stock markets," *Expert Syst. Appl.*, vol. 163, p. 113761, 2021, doi: 10.1016/j.eswa.2020.113761.

[16] B. Jin, "An intelligent algorithmic trading based on a risk-return reinforcement learning algorithm," *ArXiv*, vol. abs/2208.10707, 2022, doi: 10.48550/arXiv.2208.10707.

[17] N. Darapaneni *et al.*, "Stock Price Prediction using Sentiment Analysis and Deep Learning for Indian Markets."

[18] N. Gurung, R. Hasan, ✉ Md, S. Gazi, and M. Zahidul Islam, "Journal of Business and Management Studies Algorithmic Trading Strategies: Leveraging Machine Learning Models for Enhanced Performance in the US Stock Market," 2024, doi: 10.32996/jbms.